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Understanding route switch behavior: an analysis using GPS based data

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Abstract

The objective of this paper is to study route switch behavior to detect which trip and individual characteristics most influence the choice of multiple routes for the same origin-destination (OD) trip. In this study we used a database of 361 morning commute trips, regarding 66 users, collected in the metropolitan area of Cagliari (Italy) during the "Casteddu Mobility Styles" survey. Data were collected for a 14 days period through a personal probe system called Activity Locator (Meloni, et al., 2011), a smartphone that integrates a GPS logger for the acquisition of the routes and an activity/travel diary. Mixed logit models are estimated, in order to take into account the variability of user perception. Results show that route switch behavior is influenced by the number of traffic lights per km, percent of highways, time perception, gender, age, individual income and driving experience in relation with the minutes per km.

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Keywords: Route choice; Route switch; GPS;

1. Introduction

Understanding road user behavior is essential for the design, implementation, and operation of a transportation system. For this reason, many researchers (Prato, 2009; Bovy, 2009; Tawfik, et al., 2010) have focused their attention on route choice behavior. This is the most complex of all travel choice decisions to interpret, also because it is influenced by habit, repetitive behavior that remains relatively unchanged over time and space, especially for

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home to work trips (in which experience provides users with a good knowledge of the road network), and in terms of spatial characterization. Contrary to other travel choices (such as modal choice), the number of alternatives can be very large, leading to the possibility of overlaps, that gives rise to inter-correlation (Bovy, 2009). Also, due to the difficulties to know the actual route choice of the individual, understanding route choice needs the acquisition of those individual characteristics that are not directly observable in aggregate data. In the past, route choice information was acquired through phone calls, e-mails or face-to-face interviews, whereby users provided information about the chosen route (Ben-Akiva, et al., 1984; Mahmassani, et al., 1993; Ramming, 2001; Prato, et al., 2005). As user memory largely influences stated choice data, they are often inaccurate and unreliable (Murakami and Wagner, 1999; Barbeau, et al., 2009). Technological progress, combined with the rapid advances in GPS devices, has resulted in major benefits for data collection, which now can be recorded automatically, in electronic format and, more importantly, with greater accuracy than those collected by means of individual interviews (Murakami and Wagner, 1999; Nakazato, et al., 2006; Hato, et al., 2006; Bricka, et al., 2009; Barbeau, et al., 2009). GPS has also been used to improve the knowledge of the attributes governing route choice (Jan, et al., 2000; Li, et al., 2005; Parkany, et al., 2006; Papinski, et al., 2009; Zhu and Levinson, 2009; Papinski and Scott, 2010; Zhu and Levinson, 2010; Spissu, et al., 2011; Levinson and Zhu, 2013).

The interpretation of the behavioral aspects involved in route choice is a fairly broad research area and comprises several theories, which have developed both the classical discrete choice models (Ramming, 2001; Wolf, et al., 2004; Bekhor, et al., 2006; McFadden, 2001; Prato, et al., 2012), both the learning based models (Fudenberg and Levine, 1998; Erev, et al., 1999; Bogers, et al., 2005), and those based on the prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Avineri and Bovy, 2008; Xu, et al., 2011). In this study we focused the attention on a particular aspect of route choice behavior, known as route-switching. It consists on the fact that users, moving between the same OD pair, do not always use the same route, but change, depending on the level of satisfaction of several elements that are not directly known to the researcher (Abdel-Aty, et al., 1994; Li, et al., 2005; Zhu and Levinson, 2010; Tawfik, et al., 2010; Spissu, et al., 2011). Several studies have shown the particular behavior in relation to the choice of different routes for the same OD trip. Abdel-Aty et al. (1994), using CATI survey data (944 morning commuters in the Los Angeles area) have shown that about 5% of users take more than one route for trips between the same OD pair, that differs substantially from the 60% found by Li et al. (2005) (10 days GPS survey for 182 Atlanta commute drivers). Zhu and Levinson (2009) report 67.5% route changers (GPS data for 35 morning commuters and 351 trips in the Twin Cities area), while Levinson e Zhu (2013) observed about 40% (GPS survey, 95 commuters and 657 home to work trips, Twin Cities area). Spissu et al. (2011), based on a GPS survey in the metropolitan area of Cagliari (Italy, all purpose, 12 users and 293 trips) observed 7% route changers, while Arifin and Axhausen (2011) found that 34.5% of users change routes (Jakarta, 93 users, 601 trips, 212 of which by car and 195 by bike, collected with GPS). Thus, clearly there is substantial variability which depends on both the context in which data are collected and on trip characteristics, as well as on the users themselves. All these researchers, except Li et al. (2005), only noticed this particular behavior and didn’t investigate more in depth. Other researches (Khattak, et al., 1995; Mannering and Kim, 1994; Polydoropoulou, et al., 1996; Srinivasan and Mahmassani, 2003; Jou, 2004; Xu, et al., 2010; Ben-Elia and Shiftan, 2010), instead, try to model it but they mainly focused the attention on the user’s response on the route information provision. Furthermore, they database are not GPS based but are collected through questionnaires or laboratory experiments. So there are two fields that analyze the route switching behavior: the one that noticed it using GPS data and the other that try to understand it applying models to not GPS data.

The objective of this paper is then to combine the two fields of the research on route switching, trying to understand it estimating discrete choice models using a GPS based database, closing the gap of the previous researches. The final goal of the model estimations is to understand which are the main attributes of the routes and the characteristics of the users that most influence the choice of multiple routes for the same origin-destination (OD) trip. The database refers to 361 trips, concerning 66 users collected in the metropolitan area of Cagliari (Italy) during the “Casteddu Mobility Styles” (CMS) survey. It was conducted between February 2011 and June 2012 in Cagliari, Italy (Casteddu is the old name of Cagliari). It is a pilot study, above a limited number of users, of a voluntary travel behavior change program. Data were collected over 14 days using a personal probe system called Activity Locator (Meloni, et al., 2011), developed by CRiMM (Centre for Research on Mobility and Modeling – University of Cagliari), a smartphone with integrated GPS logger for acquiring routes and an activity/journey diary into which users enter the information about the activities or movements they are about to undertake. Mixed logit models were estimated for data analysis, in order to take into account the variability of user perception.

The paper is organized as follows: the second section contains a brief summary of earlier research on route switch; the third section describes data and the methodology; the fourth the results obtained while the last section provides the conclusions.

2. Earlier approaches

Several researchers have studied route switch behavior, on different days, in order to assess their sensitivity to information about traffic/road conditions (congestion, travel time reliability, delays). These aspects are also analyzed in relation to individual characteristics, such as experience on one particular route, perception of time and delays, habits, differences in age and gender. Most of the research in this field has addressed route switch behavior in relation to the provision of information, with the result that the variability of choice behavior is studied through an external intervention and not as an intrinsic characteristic of the choice mechanism. The main studies on route switch with information provision are briefly described below.

Khattak et al. (1995) studied the phenomenon in the Chicago area, analyzing 700 questionnaires concerning morning commute trips, and estimating an ordered probit model. They found that congestion, as well as a knowledge of the available alternatives increase the probability of multiple path choice, which decreases when the same route is used. They also found that high income individuals, perhaps because of the greater emphasis placed on the value of time, tend to choose more than one route, while males tend to change more than females. Mannering and Kim (1994) use an ordered logit, using data from a survey in the Interstate 5 (I-5), Seattle. The questionnaires provide a total of 2182 usable records that show how for home-to-work trips about 26% of users do not always use the same route. They found that the rate of route change increases with daily commute time, flexibility in departure and arrival times, for males and with the number of known routes, while it decreases with route journey time, delays, and income. Polydoropoulou et al. (1996), explore the reactions in the case of unexpected congestion and when information provided by ATIS systems is qualitative, quantitative, predictive or prescriptive, using questionnaire data. They estimated a binary logit, finding that the most important variables for decision change are the expected delay along the usual route, journey time of alternative routes, the level of congestion and the sources of information. They observed that drivers are less likely to change route on their home-to-work commutes, a result that is consistent with the findings of Jou and Mahmassani (1996) who detected a greater propensity to change for evening commutes. Srinivasan and Mahmassani (2003) applied dynamic logit kernel (mixed logit) models to data obtained through a laboratory experiment (55 repetitions per user), with the possibility of taking into account choice heterogeneity and their intercorrelation. In the experiment, on a sample of 134 commuters in the city of Austin, each participant had to travel from home to work for 12 simulated days. In addition to the variables directly related to the type of information provided (nature and type, feedback effects, generic attributes), time savings, the level of congestion and the cost of change (in miles) are particularly significant. Jou (2004) used a model that combines measurement and structural equations (latent variables). They analyzed questionnaire data containing a total of 553 usable records. They estimated binary logit models, finding as statistically significant age, habit, length, frequency and urgency of the trip. They concluded that, given the number of work trips, drivers tend to be more familiar with the routes they use, a factor that involves a decision made in advance, making route change difficult. Xu, et al. (2010) studied the impact of traffic information on route choice behavior for different departure times. Data refer to a SP survey, for users traveling from home to work in the morning, in Nanjing, Jiangsu, China, collecting a total of 247 usable data. For the analysis they used a multinomial logit and found that males and young people are more likely to change route (influenced by information), as well as experienced drivers. Moreover, travel time variability is particularly significant. The level of congestion instead presents a negative sign. Ben-Elia and Shiftan (2010) conducted a laboratory experiment for the application of a learning based model. They used a mixed logit with panel data on a sample of 49 participants, divided into "informed" and "uninformed”. It was found that information and experience have a combined effect on drivers’ route-choice behavior. Informed participants had faster learning rates and tended to base their decisions on memorization relating to previous outcomes whereas non-informed participants were slower to learn, required more exploration and tended to rely mostly on recent outcomes. Informed participants were more prone to risk-seeking and had greater sensitivity to travel time variability. By comparison, non-informed participants appeared to be more risk-averse and less sensitive to variability.

Another aspect that characterizes these works is the fact that behavior is acquired through questionnaires or laboratory experiments, but the validity of the results is limited, however, because the observed preferences may be affected by the lack of realism, the subjective perception and of the abstractness of choice situation (Carrion and Levinson, 2012).

In recent years, GPS systems have provided a substantial contribution to this topic, through automatic data acquisition, low costs, high precision and complete freedom for the user. As far as we aware, the only research work that studies route switch as an intrinsic feature of choice behavior without providing information is by Li et al. (2005), who also use data collected with GPS for morning commute trips, in order to assess which route attributes and socio-economic characteristics of the users have the greatest importance in determining whether a user is a "changer" or it always uses the same route. The sample was derived from an in-vehicle GPS survey, known as "Commute Atlanta", and they chose a sub-sample from the database for a 10- day period, concerning 182 drivers belonging to 138 households, whose socio-economic characteristics are known. They estimated 4 binary logit models: one that included just the trip information, one with the characteristics of the main route (the most used during the survey), the third the socio-demographics and the fourth incorporating all the variables simultaneously. The results show that the greater significance is to be found in the number of intermediate stops during the trip, flexibility in arrival time at work and the user's age.

The present research is placed in the latter context, analyzing in particular route choice made by the individual in the absence of external stimuli, detected through a GPS system.

3. Data description and methodology

The data utilized in this study were collected during the "Casteddu Mobility Styles" survey, for a sample of 109 individuals, where each participant was asked to carry a smart phone with built-in GPS in which an application called "Activity Locator" – implemented by CRiMM – had been installed (for more information see also Meloni, et al., 2011). This device permitted users to send activity and travel attributes to a dedicated server in real time, together with automatic positioning points (timing, latitude, longitude). At the end of the survey all the information gathered was reworked into a single activity-travel database.

The "Activity Locator" system comprises (a) a client software installed in a portable Gps-integrated device, (b) a server software that transmits and receives information to/from each client, and (c) an Internet connection. The client software is a Java application that can be installed in any smartphone (Symbian, Android and IOS6 platform) with built-in GPS currently available on the market. The application enables to track individual daily routes and to collect all activity-travel related information through a sequence of pull-down menus that reproduces the classical activity diaries, but in real time. The application is accessible from the cell phone "home" screen, pressing a dedicated key, and is designed to send automatic pings every 5 seconds containing only positioning data (latitude, longitude, time) and manually inserted attributes of activities and trips. The server software collects the information sent by each client. Each user can be identified in real time on a map (powered by Google Maps) by a symbol containing all the user information (i.e. spatial, temporal, and activity information codes). The data are immediately available in database formats (i.e. .xls, .csv, .xml) and downloadable onto any desktop or laptop computer. The data are transferred by each client to the server and vice versa via an Internet connection. In addition, the server software is designed to send a variety of information to the clients such as traffic information and survey requirements. Each GPS track (consisting of a sequence of referenced position points) was then treated with map-matching techniques, through which it was possible to associate each "GPS point" to a link of the network, thus creating the observed route database (Corona et al., 2012).

We registered several errors due to the use of the Activity Locator. These could be distinguished into user errors and system errors. The user errors are mostly related to misreported activity data, which include omissions, inconsistencies and deferments in manually reporting activity and trip attributes; focusing on the system errors, these are mainly due to technical issues such as canyon effects, signal reflection and smartphone life battery. Also, internet errors related to connection issues that prevented data transfer between the smartphones and the server have been encountered. The interested user could read Meloni and Sanjust (2014) for more information about.

During the survey weeks a total of 8831 trips were recorded by 109 individuals, of which 4791 referring to the car driver mode. For the purpose of analysing all the morning commute trips, we selected all those with start time between 7:00 and 10:00 am, for a total of 626 trips (concerning 95 users), which in a previous research were also compared with those simulated using a macrosimulation model (Vacca and Meloni, 2013). Out of this total, only 361 trips, regarding 66 users, had the characteristics of repetitive commute (home-to-work) trips, where 29% of users chose more than one route for the same OD trip. The data are summarized in table 1, which shows all the characteristics of the sample.

Table 1 - Sample characteristics

Route	N°	Ave.	Std. Dev
Average V/C ratio		*0.62*	*0.21*
Percentage of route where V/C > 0.8		*0.30*	*0.21*
Number of traffic lights per km		*0.56*	*0.58*
Percentage of route consisting of highways		*0.33*	*0.28*
Percentage of route consisting of inter-district roads		*0.36*	*0.27*
Travel time in minutes		*18.48*	*10.77*
Route length		*8.13*	*7.01*
Least cost set	*153*		
Trip	**N°**	**Ave.**	**Std. Dev**
Difference in departure time vs average		*0.02*	*12.69*
Number of trips started in advance	*46*		
Number of trips started late	*42*		
Household	**N°**	**%**	
Children	*21*	*31.8%*	
Household members			
1	*9*	*13.6%*	
2	*16*	*24.2%*	
3	*15*	*22.7%*	
4	*20*	*30.3%*	
5	*6*	*9.1%*	
Number of cars per household			
1	*13*	*19.7%*	
2	*34*	*51.5%*	
3	*14*	*21.2%*	
4	*3*	*4.5%*	
5	*2*	*3.0%*	
Car type			
Sedan	*8*	*12.1%*	
Two seater	*5*	*7.6%*	
Station Wagon - minivan	*4*	*6.1%*	
Economical	*49*	*74.2%*	

User - Age group	N°	%
18 - 30	*19*	*28.8%*
31 - 40	*26*	*39.4%*
41 - 60	*21*	*31.8%*
61 - 80	*0*	*0.0%*
User - Gender	**N°**	**%**
Male	*30*	*45.5%*
Female	*36*	*54.5%*
User - Occupation	**N°**	**%**
Student	*7*	*10.6%*
Employee	*40*	*60.6%*
Self-employed	*17*	*25.8%*
Unemployed	*2*	*3.0%*
User - Education	**N°**	**%**
High school graduation	*20*	*30.3%*
Professional specialization	*4*	*6.1%*
Degree	*26*	*39.4%*
Post Degree	*14*	*21.2%*
Primary school	*2*	*3.0%*
User - Monthly income	**N°**	**%**
Less than €1000	*16*	*24.2%*
€1000 - €2000	*29*	*43.9%*
€2000 - €4000	*12*	*18.2%*
More than €4000	*4*	*6.1%*
Don't know	*1*	*1.5%*
Don't have	*4*	*6.1%*
User - Km/Year	**N°**	**%**
Less than 15,000 km	*33*	*50.0%*
15,000 – 25,000 km	*15*	*22.7%*
More than 25,000 km	*10*	*15.2%*
Don't know	*8*	*12.1%*
User - €/month for transport	**N°**	**%**
Less than €50	*8*	*12.1%*
€50 - €100	*29*	*43.9%*

	€100 - €300	*25*	*37.9%*
	More than €300	*2*	*3.0%*
	Don't know	*2*	*3.0%*

We considered two different types of variables: the level of service and the socio-economic ones. The first were further divided into route and trip, the second into two sub-groups related to the individual and to the household. As far as the level of service is concerned, the difference, in minutes, between the time of departure and the average (the average is calculated, for the single user, as the one between every departure time), the average volume/capacity (V/C) ratio, the percentage of route where V/C > 0.8, number of traffic lights per km, the percentage of route consisting of highways or inter district roads, travel time, the distance and minutes per km of travel are considered to be continuous, while starting out earlier or later than usual and routes belonging to the least cost or shortest distance set are considered as dummies. The 0.3% of the trip length is along congested roads (V/C > 0.8), that although is not so high, could strongly influence the travel time. Furthermore, in congested links there is a high queuing probability, forcing the users to spend time while stopped, that may lead them to look for different routes, so this is the reason why this variable is taken in account. The socio-economic variables have been identified referring to earlier research, from our assumptions and from information provided by users when completing the questionnaires, structured in such a way as to take into account any differences in preference between the different groups. All variables regarding the user are considered as dummies, in accordance with the categories shown in table 1, and the children and car class likewise, while the others are all codified as continuous. In addition to the listed variables, in the literature other are shown to be particularly important, such as the number of intermediate stops and the reliability of travel time. For example, Li et. al (2005) showed that the propensity to choose multiple paths between an OD pair increases proportionally with the number of intermediate stops along the way, while travel time reliability is often used in route choice also in other research areas. Unfortunately, the database used did not allow calculating these variables. It is our intention, in a forthcoming research, to test these variables expanding the database to the entire day, thus using all the route information already available.

3.1. Methodology

Due to the characteristics of the data, a discrete choice model has been constructed to assess the dynamics of route switch. The chose specification is the mixed logit (ML) one (Ben Akiva and Bolduc, 1996; McFadden and Train, 2000), in order to consider the difference of perception to some particularly sensitive variables and of subjective interpretation (e.g., time). Furthermore, due to the availability of informations of repeated choices by the same user, with the ML is also possible to take into account of the panel effect. These types of models are particularly effective in investigating route switch, as demonstrated by Han, et al. (2001), Srinivasan and Mahmassani (2003), Ben-Elia and Shiftan (2010), previously discussed. The basic structure of the ML is the same as all discrete choice models typically used in the transportation sector, considering the random term composed of more than one component, of which at least one ε_{jq} is IID Gumbel distributed and a η_{jq} which could assume any distribution and allows to model several phenomena such as the correlation between the alternatives and users, heteroschedasticity, random heterogeneity in preferences, etc.. Thus the ML has the following specification (Train, 2009):

$$U_{jq} = \theta x_{jq} + \eta_{jq} + \varepsilon_{jq} \quad (1)$$

In this study, the dependent variable represents the fact that the actual route is the most chosen, by the user, moving through the same OD during the am peak hour of the survey period. So, it assumes the value of 1 if the actual route is the most frequent chosen, 0 otherwise. So, the estimated model is a binary mixed logit, with the goal to understand the role which some attributes of the trips and some characteristics of the users play on the route switching behavior. Starting from the above described theory we developed a specific code language of the GAUSS software to estimate the different models

4. Model results

We estimated different model specifications testing all the available variables, in order to identify the most significant ones. However, most probably due to small size of the sample, not all of them are statistically significant. In the following chapter, by the way, we report a comment related to each tested variable, while at the end the results of a model estimated using only the most significant ones are reported.

The estimates show that the number of traffic lights per kilometer and the percentage of highways are particularly significant, with negative and positive sign respectively. This confirms that users prefer routes with few traffic lights and highways and inter district roads. Belonging to the least cost route set also has a positive sign and a high significance, showing that if the route is also mathematically the least cost path it is more likely to be favored by users. The explanation for this is in agreement with the findings of previous research, i.e. that users have a good perception of both time and distance (Vacca and Meloni, 2013). Interestingly, though not statistically significant, the signs associated with the variables starting out earlier or later than usual are positive and negative respectively. This indicates that when commuters leave home later than usual, they take their habitual route, probably because choosing a known route ensures they will arrive at work on time. The same holds for the (positive) sign associated with the difference in minutes of departure time, which confirms the choice of the usual route when leaving home later. The travel time and distance were not significant, likewise the minutes per km. The latter has a positive sign, suggesting that routes with longer travel times tend to be considered as habitual. This is further confirmed in the signs of the variables concerning congestion (average V/C and V/C greater than 0.8, not significant), both positive, indicating that the most congested routes are also the most used. There is no simple explanation for this as in some cases the choice may be obligatory due to unawareness or lack of viable alternatives. Moreover, the effects of habit and familiarity may play a significant role in route choice, leading users to opt for routes that, though congested, are considered safer and known. Two other variables that are not significant are the percentage of inter-urban roads and belonging to the least distance set, both with negative signs. The explanation for the second lies in the fact that users perceive the spatial characteristics of the path very well and as a result tend to choose the route with the shortest distance. Inter-district roads by contrast account for a very high percentage of the Cagliari metropolitan area, so it is possible that when choosing an alternative route a substantial portion is made up of these roads. The variability in perception of the same variable by different users was also estimated, finding that only the minutes per km is significant (distributed as standard normal), a clear sign of how users interpret this value differently and further demonstration of the important role of individual perception in decision making. Among those variables relating to age, the most significant group is between 18 and 30, with a positive sign, indicating that this group of users always tend to use the usual route. Interestingly the sign of the 31 to 40 age group is negative, indicating that this group has a greater propensity to choose multiple paths, probably as they are more experienced drivers. As far as gender is concerned, the estimates have shown that males tend to use more than one route, also presenting a good statistical significance justifiable, also in this case, with a better knowledge of the network compared to their female counterparts. Similarly to the other categories of socio-economic variables, no statistical significance has been found for occupation, the number of kilometers driven per year, individual income, monthly expenditure for transport and car class. Some interaction variables were also tested, with the aim of evaluating the influence of the level of service and trip indicators for particular classes of users. It has been found that, compared with the increase in minutes per km, users who drive between 15,000 and 25,000 km a year, and those with an individual income of over € 4,000 per month, have a greater propensity to change route, indicating for the former that driving experience and the greater knowledge of the network (and thus of alternative routes) play a major role in route choice. For the latter, however, the cause is probably to be sought in the greater importance these users give to travel time. Table 2 summarizes the modeling results, where only the significant variables are included in the final specification.

Table 2 - Model results

Variable	Estimation	t-test
Level of service		
Number of traffic lights per km	*-1.4516*	*-3.644*
Percentage of route consisting of highways	*4.293*	*3.985*
Sigma minutes per km	*0.3684*	*2.093*
Least cost set	*2.712*	*3.85*
Socio-econimic		
Age from 18 to 31	*1.6516*	*2.765*
Males	*-1.1623*	*-1.442*
Interaction		
Minutes per km for 15000-25000 km	*-0.3493*	*-1.671*
Minutes per km for more than €4000 /month	*-0.6242*	*-1.481*
Constant	*1.7667*	*2.966*
Observations	*361*	
Users	*66*	
Final Log Likelihood	*-15.9880*	

5. Conclusions

This paper, unlike most research work that has focused on route switch with information provision, addresses the analysis of route choice behavior in the absence of external stimuli. GPS data were analyzed for morning home-to-work commute trips in the metropolitan area of Cagliari, with the aim of identifying which route, trip and individuals' socio-economic characteristics determine the choice of multiple routes for the same OD trip. It was found that about 29% of the users use more than one path, about half of those found by Li et al. (2005) (60%, with data acquired via GPS) and a little less than those reported by Levinson and Zhu (2013) (40%, GPS data). The mixed logit model estimates showed that the number of traffic lights per km (negatively), the percent of highways (positively, as also found by Zhu and Levinson (2010)) and belonging to the set of least cost paths (positively) affect the fact the choice of habitual route. The level of congestion, instead, shows a positive influence, in agreement with the results reported by Srinivasan and Mahmassani (2003), who justify this finding with the difficulty of re-routing in the network. Among the socio economic variables, it was found that males are more likely to change route, in agreement with the findings of several workers (Khattak, et al., 1995; Mannering and Kim, 1994; Han, et al., 2001; Xu, et al., 2010). Interestingly the change in perception of the minutes per km has particular statistical significance, further confirmation of how differences in user perception are particularly significant in choice behavior. Furthermore, it was found that driving experience leads to a greater propensity to route change, so a better knowledge of the network also affects commute trips choice, that tend to be less subject to change. It should be emphasized that this study is the initial phase of a broader research project that aims to analyze route switch considering the trips made throughout the day (not just morning commute trips), so as to test the effects of the times trips made, of time reliability, of the day and, possibly, of different motivations. Furthermore, the presence or not of secondary trips could be important, and it is also possible to collect this information from our activity/travel diary. We didn't considered it in this paper because in this sample there are only home to work trips, without intermediate stops. We are looking forward to include this variable in the future research, when we should be able to use the entire sample. Another area of investigation concerns the development of a learning based model, aimed at determining the effects of previous choices (and therefore experience) on current choices and therefore to assess the correlation. The findings could be interesting for developing algorithms for calibrating choice set generation models.

The results of the present work suggest several aspects to take into account when estimating route choice models. The first it is obviously related to the use of GPS data instead of other kind of data. Indeed, with the possibility to know the actual chosen route by the users, it is possible to evaluate and take into account about some variable and aspects directly related between the road network and how the users use it. For example, this work showed how the percentage of route consisting in congested roads or highways play an important role in the choice context. It also important to distinguish the typology of the trip, because has been shown that for commute trips users have a more sensibility to time and distance, compared to other reason trips. Also, this work confirms that user-related variables, like habit and experience, can strongly influence the choice behavior of the users, so it is useful to include them (when possible) in the model specifications.

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